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Robust Face Recognition under Difficult Lighting Conditions

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***Abstract*— This paper addresses the problem of illumination effects on Face recognition and works for an approach to reduce their effect on recognition performance. More broadly, a simple and efficient preprocessing chain that eliminates most of the effects of changing illumination while still preserving the essential appearance details that are needed for recognition. Using local ternary patterns (LTP), a generalization of the local binary pattern (LBP) local texture descriptor that is more discriminant and less sensitive to noise in uniform regions. We also show that replacing comparisons based on local spatial histograms with a distance transform based similarity metric further improves the performance of LBP/LTP based face recognition; and Robustness is still improved by adding Kernel principal component analysis (PCA) feature extraction.**

Keywords- Face recognition, local ternary patterns, local binary pattern, and Kernel principal component analysis

I. INTRODUCTION

This paper focuses mainly on the issue of robustness to lighting variations. For example, a face verification system for a portable device should be able to verify a client at any time (day or night) and in any place (indoors or outdoors). Unfortunately, facial appearance depends strongly on the ambient lighting Traditional approaches for dealing with this issue can be broadly classified into three categories: appearance-based, normalization-based, and feature-based methods. In this paper, we propose an integrative framework that combines the strengths of all three of the above approaches. The overall process can be viewed as a pipeline consisting of image normalization, feature extraction, and subspace representation, as shown in Fig. 1. Each stage increases resistance to illumination variations and makes the information needed for recognition more manifest. The method centres on a rich set of robust visual features that is selected to capture as much as possible of the available information. A well-designed image preprocessing pipeline is prepended to further enhance robustness. In this paper, combinations of all the above approaches are used. The schematic representation of the whole framework is given as follows, which contains preprocessing stage, feature extraction stage and subspace representation stage for recognition.

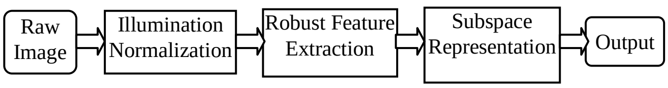

Figure 1. Stages of Face Recognition Method

II. ILLUMINATION NORMALIZATION

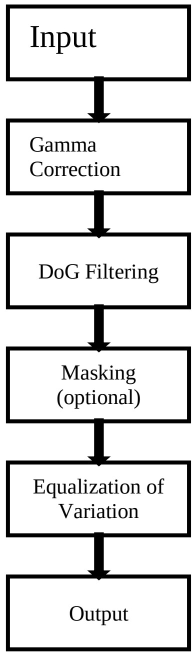

Figure 2. Stages of our image preprocessing pipeline

Gamma correction – An initial level of corrections are made for illumination deficiency. However this does not remove the influence of overall intensity gradients such as shading effects

Difference of Gaussians (DoG) Filtering – This involves the subtraction of one blurred version of an original gray scale image from another less blurred version of the original. This enhances the fine details of the image.

Masking – At this stage, irrelevant regions like of the images are masked out.

Equalization of Variation (EoV) – At this stage, intensities of the image are rescaled. This step is required to standardize the intensity values for further processing.

III. TEXTURE BASED FEATURE EXTRACTION

A. *Local Binary Patterns (LBP)*

LBP operator summarizes local gray-level structure. The operator takes a local neighborhood around each pixel, thresholds the pixels of the neighborhood at the value of the central pixel and uses the resulting binary-valued image patch as a local image descriptor.

LBP's are resistant to lighting effects and are shown to have high discriminative power for texture classification [5]. However, they are sensitive. Given that many facial regions are relatively uniform, it is potentially useful to improve the robustness of the underlying descriptors in these areas.

It was originally defined for 3x3 neighborhoods, giving 8-bit integer LBP codes based on the eight pixels around the central one. Formally, the LBP operator takes the form

$$LBP(Xc,Yc)=\sum_{n=0}^{7}2^{n}S(in-ic)\text{.............}(1)$$

where in this case runs over the 8 neighbors of the central pixel , and are the gray-level values at and , and is 1 if and 0 otherwise. The LBP encoding process is illustrated in Fig. 3.

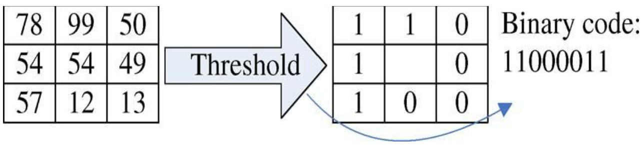

Figure 3. Basic LBP operator

B. *Local Ternary Patterns (LTP)*

LTP, which are derived from LBP, are also used. In this gray-levels in a zone of width ±t around a center pixel are quantized to zero, ones above this are quantized to +1 and ones below it to −1.

Thus obtained LBP and LTP are used as texture feature descriptors.

LBPs have proven to be highly discriminative features for texture classification and they are resistant to lighting effects in the sense that they are invariant to monotonic gray-level transformations. Many facial regions are relatively uniform and it is legitimate to investigate whether the robustness of the features can be improved in these regions. This section extends LBP to 3-valued codes, LTP, in which gray-levels in a zone of width around are quantized to zero, ones above this are quantized to 1 and ones below it to 1, i.e., the indicator is replaced with a 3-valued function and the binary LBP code is replaced by a ternary LTP code. Here is a user-specified threshold—so LTP codes are more resistant to noise, but no longer strictly invariant to gray-level transformations. The LTP encoding procedure is illustrated in Fig. 4. Here the threshold was set to 5, so the tolerance interval is

$$s'(u,ic,t)=\left\{\begin{array}{ll}1 & u\geq ic+t\\ 0 & u-ic+t\\ \text{-1} & u\leq ic+t\end{array}\right.\qquad(2)$$

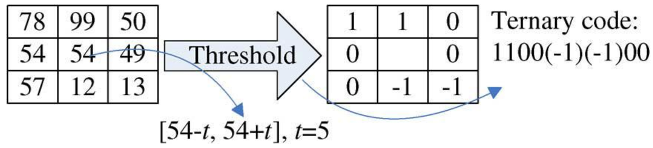

Figure 4. Illustration of the basic LTP operator.

When using LTP for visual matching, we could use valued codes, but the uniform pattern argument also applies in the ternary case. For simplicity, the experiments below use a coding scheme that splits each ternary pattern into its positive and negative halves as illustrated in Fig. 5, subsequently treating these as two separate channels of LBP descriptors for which separate histograms and similarity metrics are computed, combining the results only at the end of the computation.

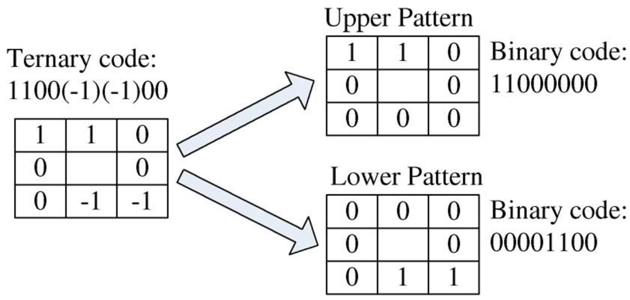

Figure 5. Splitting an LTP code into Positive and Negative LBP codes.

C. *Distance transform based Similarity Measure*

The used similarity metric is an LBP based method for face recognition [6] that divides the face into a regular grid of cells and histograms the uniform LBP's within each cell, finally using nearest neighbor classification in the χ2 histogram distance for recognition:

$$X^{2}(p,q)=\sum_{i}\frac{(pi-qi)^{2}}{(pi-qi)}\qquad(3)$$

Here p,q are image region descriptors (histogram vectors), respectively

However, subdividing the face into a regular grid seems somewhat arbitrary: the cells are not necessarily well aligned with facial features, and the partitioning is likely to cause both aliasing (due to abrupt spatial quantization of descriptor contributions) and loss of spatial resolution (as position within each grid cell is not coded). Given that the overall goal of coding is to provide illumination- and outlier-robust visual correspondence with some leeway for small spatial deviations due to misalignment, it seems more appropriate to use a Hausdorff- distance-like similarity metric that takes each LBP or LTP pixel code in image and tests whether a similar code appears at a nearby position in image , with a weighting that decreases smoothly with image distance. Such a scheme should be able to achieve discriminant appearance-based image matching with a well-controllable degree of spatial looseness. We can achieve this using distance transforms. Given a 2-D reference image, we find its image of LBP or LTP codes and transform this into a set of sparse binary images , one for each possible LBP or LTP code value (i.e., 59 images for uniform codes). Each specifies the pixel positions at which its particular LBP or LTP code value

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appears. We then calculate the distance transform image of each . Each pixel of gives the distance to the nearest image pixel with code (2-D Euclidean distance is used in the experiments below). The distance or similarity metric from image to image is then

$$D(X,Y) = \sum_{pixels(i,j)\text{ of Y}} w(d_X^{K\,y}(i,\ j)(i,j)) \quad (4)$$

Here, is the code value of pixel of image and is a user-defined function4 giving the penalty to include for a pixel at the given spatial distance from the nearest matching code in . In our experiments we tested both Gaussian similarity metrics and truncated linear distances. Their performance is similar, with truncated distances giving slightly better results overall. For 120x120 face images in which an iris or nostril has a radius of about six pixels and overall global face alignment is within a few pixels, our default parameter values were pixels and pixels.

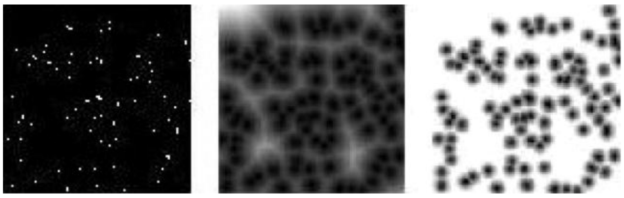
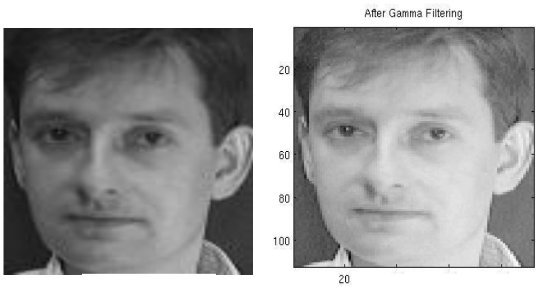


Figure 6. From left to right: a binary layer, its distance transform, and the truncated linear version of this.

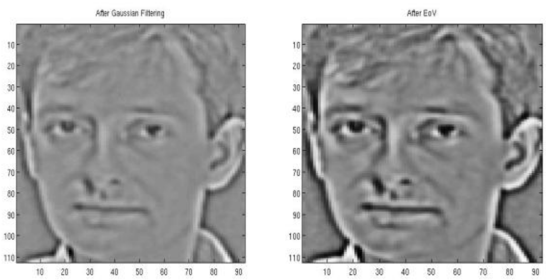
Fig. 6 shows an example of a binary layer and its distance transforms. For a given target the transform can be computed and mapped through in a preprocessing step, after which matching to any subsequent image takes (number of pixels) irrespective of the number of code values.

IV. RESULTS

Following is the results during the preprocessing stage:



(a) (b)



(c) (d)

(e) (f)

Figure 7: Pre-processing stages: (a) Original Image, (b) After Gamma filtering (c) After Gaussian filtering and (d) After EoV (e) Before Pre-processing and (f) After Pre-processing

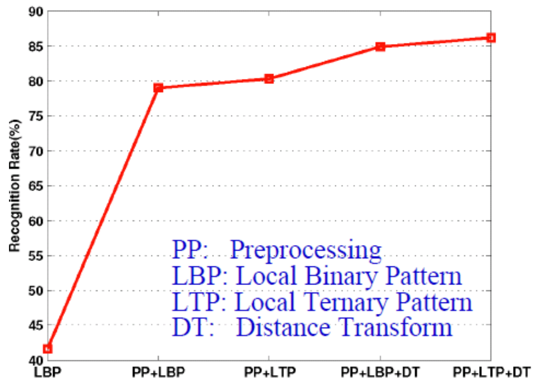


Figure 8: Experimental Results based on literature survey

V. ABBREVIATIONS AND ACRONYMS

LTP – Local Ternary Patterns

LBP - Local Binary Pattern

PCA- Principal Component Analysis

FRGC-204 - Face Recognition Grand Challenge Version 2 Experiment 4

FRVT - Face Recognition Vendor Test

FRGC - Face Recognition Grand Challenge Trials

MSR - Multiscale Retinex

SQI - Self Quotient Image

LTV - Logarithmic Total Variation

GB - Gross and Brajovic

HE - Histogram Equalization

VI. CONCLUSION

We have presented new methods for face recognition under uncontrolled lighting based on robust preprocessing and an extension of the LBP local texture descriptor. The main contributions are as follows:

1) A simple, efficient image preprocessing chain whose practical recognition performance is comparable to or better than current (often much more complex) illumination normalization methods;

2) A rich descriptor for local texture called LTP that generalizes LBP while fragmenting less under noise in uniform regions:

3) A distance transform based similarity metric that captures the local structure and geometric variations of LBP/LTP face images better than the simple grids of histograms that are currently used; and

4) A heterogeneous feature fusion-based recognition framework that combines two popular feature sets—Gabor wavelets and LBP—with robust illumination normalization and a kernelized discriminative feature extraction method. The combination of these enhancements gives the state-of-the-art performance on three well-known large-scale face datasets that contain widely varying lighting conditions. Moreover, we empirically make a comprehensive analysis and comparison with several state-of-the-art illumination normalization methods on the large-scale FRGC-204 dataset, and investigate their connections with robust descriptors, recognition methods, and image quality. This provides new insights into the role of robust preprocessing methods played in dealing with difficult lighting conditions and thus being useful in the designation of new methods for robust face recognition.

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